Using Soft Computing Technologies for the Simulation of LCAC Dynamics

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ABSTRACT

Data acquired from experiments with a 1/6th scale, free-running model of an air-cushioned, amphibious vehicle (LCAC) in waves and calm water were used to train a recursive neural network (RNN). This network is used to simulate the six degree-of-freedom motion of the LCAC, providing faster than real-time, time-domain predictions of the vehicle's dynamics as a function of the control signals given by the driver. Results are presented comparing the time-series predictions of the RNN simulation with experimental data. Two error measures are used to quantify the results, an average angle measure and a correlation coefficient, and they indicate good solutions in every case. The intent is to use this time domain simulation of LCAC to gain further insight into the vehicle's dynamics in calm water and irregular waves.

KEY WORDS

neural networks, nonlinear time domain simulation, free-running LCAC model, faster-than-real-time simulation, soft computing technology

1.0 INTRODUCTION

The Maneuvering and Control Division (MCD) of the Naval Surface Warfare Center, Carderock Division (NSWCCD) along with Applied Simulation Technologies have worked to develop a six degree-of-freedom simulation of a free-running model of the Navy's Landing Craft Air Cushion (LCAC) vehicle. This vehicle is a high-speed air-cushioned design with the mission to transport materiel from off-shore vessels onto the shore and then across the beach. A figure showing the LCAC is given in Fig. 1. The work described in this paper is in conjunction with a Seabase-to-Shore Future Naval Capabilities (FNC) program begun in FY05 by the Office of Naval Research (ONR) in cooperation with the Navy acquisition program for LCAC, PMS 377. The program extended through FY09, and it supported research initiatives for LCAC in the areas of Advanced Lift Fan and Advanced Skirt Development. The latter thrust area is subdivided into the following parts: Skirt Material, Skirt Design and Fabrication, Seakeeping Dynamics, Tow Tank (Captive Model) Testing, Free-Running Model Testing, and Maneuvering. The intention of this program is to provide necessary information in advance of the next-generation LCAC vehicle, known as the Ship to Shore Connector (SSC). Captive model testing of a 1/12th scale model of LCAC occurred in the Fall of FY07 at NSWCCD, and testing of a 1/6th scale free-running model was conducted in the Spring of FY09 by the Naval Surface Warfare Center, Panama City Division in Florida. A description of LCAC by the Federation of American Scientists (2000) follows.

> The Landing Craft Air Cushion (LCAC) is a high-speed, over-the-beach fully amphibious landing craft capable of carrying a 60-75 ton payload. Capable of operating from existing and planned well deck ships, it is used to transport weapons systems, equipment, cargo and personnel from ship to shore and across the beach. The LCAC is capable of carrying a 60 ton payload (up to 75 tons in an overload condition) at speeds over 40 knots. Fuel capacity is 5000 gallons, and the LCAC uses an average of 1000 gallons per hour. The LCAC, like all hovercraft, rides on a cushion of air. The air is supplied to the cushion by four centrifugal fans driven by the craft's gas turbine engines. The air is enclosed by a flexible skirt system manufactured of rubberized canvas. No portion of the LCAC hull structure penetrates the water surface; the entire hull rides approximately four feet above the surface. The LCAC has four gas turbine engines. Two engines operate the two shrouded reversible-pitch propellers at the rear of the vehicle, and the other two engines operate the four double-entry fans for lift. Located just forward of amidships are two rotatable elbow-shaped thrusters which are fed waste air that is bled from under the LCAC's cushion and are used to help steer the LCAC.

Fig. 1. Landing Craft, Air Cushion (LCAC)

A useful reference tome for the description of all aspects of air-cushioned vehicles is that of Mantle (1980 and 1975). In his concluding remarks (1975), he writes: "…the performance of an air cushion craft can be estimated to a high degree of accuracy, except in the case of rough water where considerable reliance is still made on empirical formulation. A surprising lack of data exists on performance in a sea state. No consistent formulation of performance exists for operation in head seas, following

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14. ABSTRACT
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seas, or seas of different wavelengths. Test programs, to date, all too frequently have not measured sea condition in consort with craft performance, hence correlation and prediction is difficult."

Since that time, full scale data describing the performance of LCAC in a seaway has been acquired, but efforts to simulate the motion of the vehicle in calm water and in waves are still at an early stage. This paper marks the end of a three-year program to develop and demonstrate a recursive neural network (RNN) software platform for the simulation of LCAC maneuvering in calm water and in waves. This effort leveraged the RNN development work that has been done for surface ships at model scale sponsored by the Independent Applied Research Program at NSWCCD (Hess, et al., 2006) as well as by ONR (Hess, et al., 2007 and Faller, et al., 2008). The LCAC captive and free-running model testing provided a unique opportunity to develop a nonlinear simulation of the dynamics of the vehicle in waves that can now be utilized to study vehicle performance and stability.

2.0 APPROACH

The development of the simulation of LCAC dynamics described here relied heavily on the technology of recursive neural networks. A recursive neural network is a computational technique for developing time-dependent nonlinear systems of equations that relate input control variables to output state variables. The key characteristic distinguishing *recursive* neural networks from *feed-forward* neural networks is the use of feedback; that is, the predictions generated at the outputs of a recursive neural network are redirected to form additional inputs to the network. A RNN can be trained to provide a faster-than-real-time, nonlinear, time-domain simulation of a vehicle responding to control-effected and environmental forcing. The availability of such a model then permits predictive and model reference control approaches to be explored.

A key advantage to employing neural networks in time-domain simulations is the fact that they are able to learn the underlying interactions that relate sets of variables. This means that unlike many hard computing techniques, neural networks do not require an *a priori* knowledge of the underlying laws that govern a given situation; instead, neural networks are able to deduce these directly from data. If prior knowledge of some of these relationships does exist, however, it can be used to improve the quality of the neural network solution. In this case, for instance, information about the model geometry was combined with raw experimental data to calculate estimates of the forces and moments acting on the LCAC model. These calculated values, along with some other raw values, were provided as the input to the network in order to present the data to the neural network in a form that would pose the problem well. This approach allows for the final RNN simulation to leverage both our theoretical knowledge of the physical interactions as well as the ability of the neural network to generate the governing system of non-linear equations.

In the original development plan, a collection of six feed-forward neural networks were to be used to provide additional inputs to the recursive network (Hess, et al., 2009). In particular, these feed-forward networks were to convert raw data describing the motion of the LCAC into predictions for six degree-of-freedom forces and moments acting on the vehicle. These networks were trained on data obtained from experiments conducted with a 1/12th scale, captive-model LCAC that was performed at NSWCCD during FY07. The rationale behind the use of feed-forward networks as inputs to the recursive network was that forces and moments act on the vehicle to produce the resulting motion and are the proper inputs for the problem. On the free-running model and on the full-scale LCAC, however, there is no system that directly measures forces and moments acting on the vessel, so these feed-forward networks were designed with the intent of mapping information describing the motions of the vehicle to predictions for the loads acting upon it.

The implicit assumption made here, of course, is that the feed-forward neural networks will only be asked to predict loads generated in conditions that are similar to the ones that were present during the collection of the training data. That is, the predictions generated by the neural network cannot be applied to situations that are dramatically different that the ones it has learned about. In this case, however, the 1/12th-scale captive-model test, which provided the training data sets for the feed-forward network, only investigated the response of the LCAC model during purely longitudinal motion (no sideslip). This ultimately caused the feed-forward networks to be ill-suited for application to the free-running model, as it was found that the motion of the free-running model often induced large sideslip angles, occasionally achieving values greater than 60 degrees. Thus, the inputs to the final RNN simulation did not include the predicted forces and moments generated by the feed-forward neural networks.

A schematic view of the recursive neural network model developed for LCAC is shown below in Fig. 2. The formulation of the LCAC simulation problem uses derived forces and moments (green box) acting on the vehicle at time t as well as raw control signals from the operator as input into the RNN. The network was trained to predict vehicle motion (in the form of the three angular and three linear velocities describing its dynamics) at time $t+\Delta t$ using the data obtained from the free-running model. The input forces and moments are calculated using control inputs, geometry information, and state variables from previous time steps and are based on known relations describing the physics of thrusters, fans, and rudders. As mentioned earlier, by converting the raw control signals into forces and moments, we provide the data to the neural network in a way that is more physically meaningful, making it easier for the RNN to accurately develop a nonlinear system of equations that describes the dynamics of LCAC.

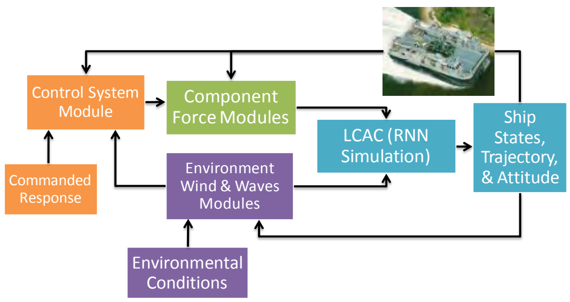

Fig. 2. Schematic of the RNN-based nonlinear simulation for LCAC

A 1/6th-scale free-running model experiment (Fig. 3), carried out from September 2008 to March 2009 in Panama City, Florida, provided the data used to develop the RNN LCAC simulation. The purpose of this experiment was to acquire data characterizing the motion of the vehicle in a variety of maneuvers and over a wide speed range in both waves and calm water.

Fig. 3. 1/6th-scale free-running LCAC model in Panama City, Florida

A list of parameters needed for the RNN simulation was provided to the experimental team and is displayed in graphical form in Fig. 4. These variables were designed to capture all of the important information concerning both the motion of the LCAC itself and the interactions that influenced that motion. A combination of experience with neural network simulations and knowledge of the underlying physics helped to inform the selection of these parameters.

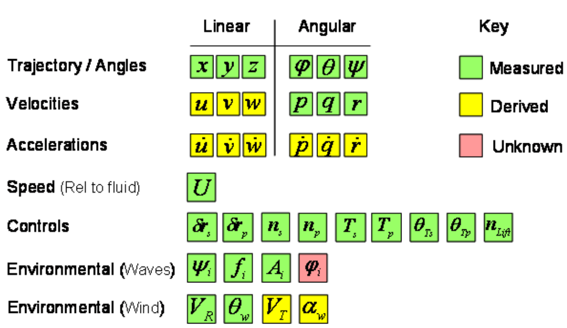

Fig. 4. Graphical view of the test parameters needed for the recursive neural network simulation

During the course of the actual experiment, the LCAC model was tested in a series of maneuvers including turns and overshoots (zigzags) in conditions ranging from calm water through sea state 3 (the most severe conditions tested were at sea state 3.75). Although certain difficulties encountered during the experiment did not allow for every requested parameter to be acquired, sufficient data was obtained to allow for the training of the recursive neural network. Some of the key measurements made during testing include: position (GPS), attitude, angular velocities, thrust fan speed, rudder deflection angle, thruster pressure, and thruster deflection angle, as well as cushion pressures and bag pressures at various locations around the model.

A subset of the described free-running model data, including data acquired during turns and overshoot maneuvers, was used to train the recursive neural network, shown schematically in Fig. 5. The final RNN simulation developed from this data generates time-series predictions for the six state variables describing the LCAC's instantaneous dynamics (u, v, w, p, q, r) as a function of the control inputs to the model: ω_{t1}, ω_{t2} (thrust fan speeds), P_{t1}, P_{t2} (thruster pressures), θ_{r1}, θ_{r2} (rudder deflection angles), θ_{t1}, θ_{t2} (thruster deflection angles), and θ_{p1}, θ_{p2} (thrust fan blade pitch angles) as well as previous values of the state variables.

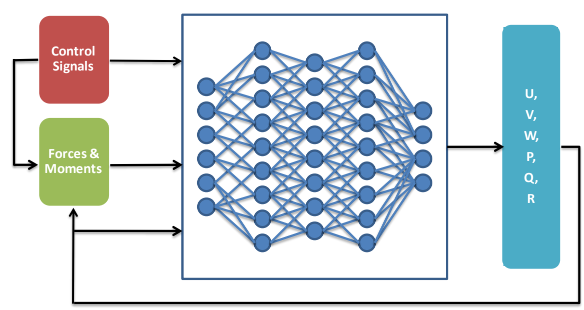

Fig. 5. Recursive neural network model of LCAC dynamics

Having predicted values for u, v, w, p, q and r, the RNN simulation then computes values for x, y, z, φ, θ and ψ forward from some initial conditions. This allows the user to obtain faster-than-real-time information from the trained network about the vehicle's predicted behavior in terms of both its aggregate displacements and attitudes (together giving trajectory information) and its instantaneous motion.

3.0 RESULTS

The subset of data taken from the free-running model experiment that was actually used to train the network consisted of seven runs, each lasting about a minute long. This corresponds to approximately 2240 ordered n-tuples, which span a range of speeds and maneuvers that were used in the training of the recursive neural network. This data was then subdivided into two groups: six of the seven training runs were used to train the neural network (training data), and one of the runs was specifically set aside to not be used during training (validation data) and was instead used to measure how well the trained neural network could generalize its predictions to maneuvers that were similar,

but still different, from the ones it encountered in the training data. The final measure of prediction quality presented here is computed using both the training and validation data, but is weighted to favor the validation data to emphasize the importance of the simulation's ability to generalize.

Included below in Table 1 are the results of two error measures used to quantify the comparisons between model predictions and the measured data: an average angle measure (*AAM*) and a correlation coefficient (*R*). Note that the *AAM* was developed at NSWCCD and is defined in the appendix. Both error measures vary between 0 and 1, with 1 representing a perfect solution and 0 representing no agreement. As can be seen from the results above, the simulation produced good results for both the training runs and the novel validation run.

Table 1. Summary of error results for recursive neural network simulation

Data Set	AAM	R	Average
Training Data	0.93	0.97	0.95
Validation Data	0.95	0.96	0.95
Combined	0.94	0.94	0.94

Graphical results characterizing important attributes of the LCAC's motion are included in Figs. 6-12. Focusing first on Fig. 6, the component figures are presented in a pattern that is consistent for all of Figs. 6-12. At top left, the measured and predicted values for forward velocity are plotted as a function of time, with the consistent convention that measured values are depicted in black and predicted values in red. Comparing these with the plots of lateral velocity, located at top right, one is able to get a sense of the unique sideslip motion that is an integral part of LCAC dynamics. At bottom left is a plot depicting the path traced out by the free-running LCAC model over the course of the maneuver, with the convention that the positive x-axis (up) is aligned with North and the positive y-axis (right) is aligned with East. The final plot, located at bottom right, shows the model's heading as a function of time. It is important to note that although the heading and path plots may appear not to agree, this discrepancy is actually a key feature of the LCAC's motion rather than an error in the data. The difference between the direction of the model's motion and the model's heading is a result of the LCAC's tendency to sideslip.

The plots in Figs 6-12, taken together, show that the recursive neural network has successfully identified a strong functional dependence of the LCAC's motion on the control signals provided to it. The fact that the simulation was able to accurately predict the vehicle's dynamics in both the training and validation runs is indicative of the fact that it has indeed captured the underlying equations governing LCAC motion. This means that the solution developed by the RNN is general, that is, it is valid for maneuvers that were not explicitly shown to the neural network during training.

As can be seen from the set of results figures, the predictions made by the neural network tend to get worse as time increases. This can be attributed to the fact that in a recursive neural network, predicted values are fed back into the network as inputs. This means that the error in those predictions is also fed back into the network. Although the learning algorithm used to train the neural network does compensate for this error, and in fact teaches the neural network to minimize the effects of this error, it is inevitable that after a long enough time the predicted values will have grown sufficiently far from the true values that the solution will begin to diverge. Nevertheless, the ability to instantaneously predict motions with this level of fidelity up to a minute into the future opens the door for advanced control and path planning applications.

4.0 CONCLUSIONS

The neural network simulation described in this paper can be implemented as a subroutine. This will allow it to be used to make faster-than-real-time, time-domain predictions of the motion of LCAC from a set of initial conditions and control inputs. Because of the simulation's ability to generalize, this RNN model can be used to obtain values of parameters describing the vehicle's motion for maneuvers that were not experimentally tested; this provides a means for studying the dynamics of LCAC over a wider range of maneuvers than were possible to explicitly test experimentally.

One of the goals of the free-running model test was to assess the fidelity and feasibility of using the $1/6^{th}$-scale LCAC model to evaluate vehicle performance in a variety of maneuvers. Despite the difficulties with the model test itself, sufficient data was provided to develop the RNN simulation and the results indicate that such a free-running model test can be used effectively to study the unique dynamics of the vehicle over a wide range of maneuvers. According to the findings of the free-running model report, the data obtained from that experiment agree well with previous data collected at other scales (including full-scale). This suggests that the simulation described in this effort can be used to accurately describe the motions of the full-scale vehicle.

Additionally, the ability of this RNN simulation to model the dynamics of the LCAC hovercraft suggests the ability to accurately model the motion of similar hovercraft designs. Because information describing the geometry of the LCAC model was incorporated into the RNN code, it may be possible to construct simulations of alternate designs by changing the values of certain geometrical parameters. It is important to note, however, that this application operates under the assumption that the equations of motion governing the new hovercraft are essentially identical to those describing the LCAC, thus extending this simulation to dramatically different ship designs is not advised.

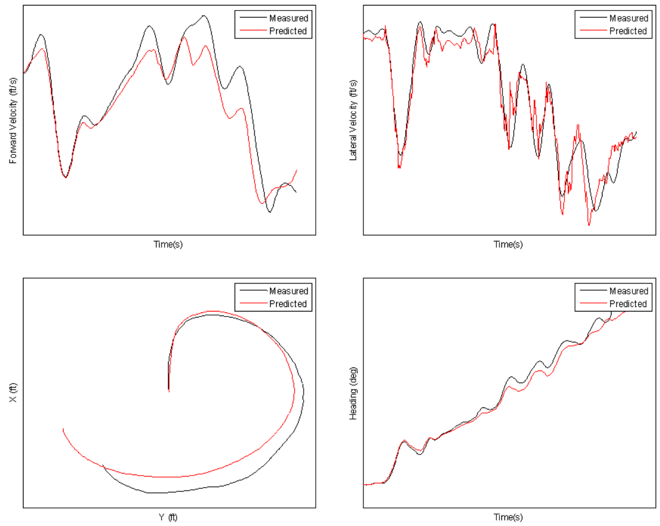

Fig. 6. Parameters characterizing a starboard turn (training data).

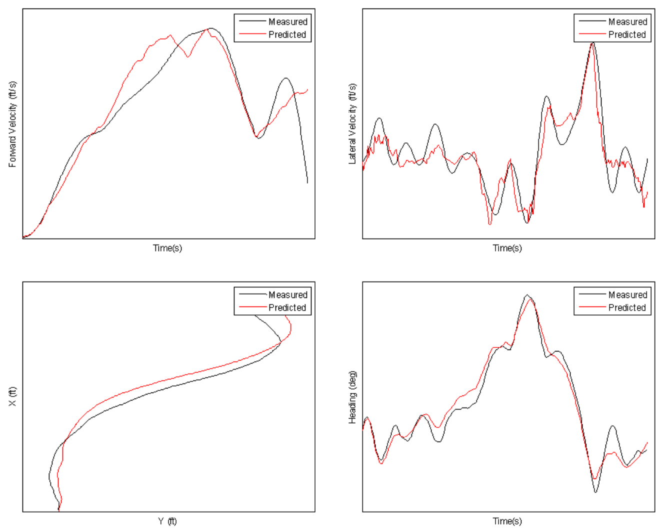

Fig. 7. Parameters characterizing an overshoot (training data).

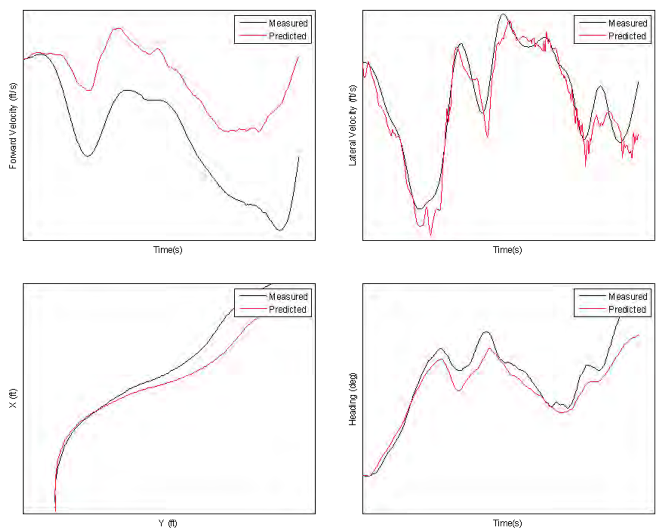

Fig. 8. Parameters characterizing a starboard turn (training data).

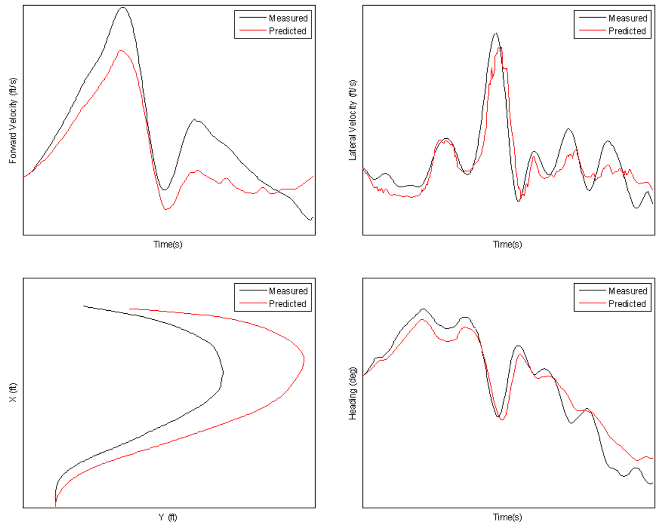

Fig. 9. Parameters characterizing a port turn (training data).

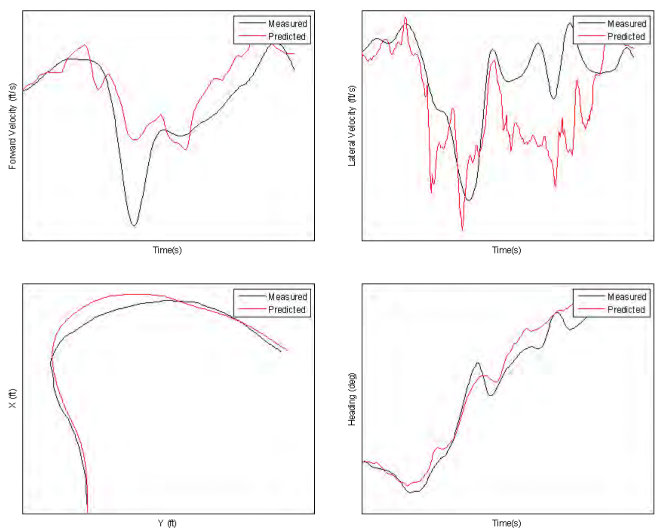

Fig. 10. Parameters characterizing a starboard turn (validation data).

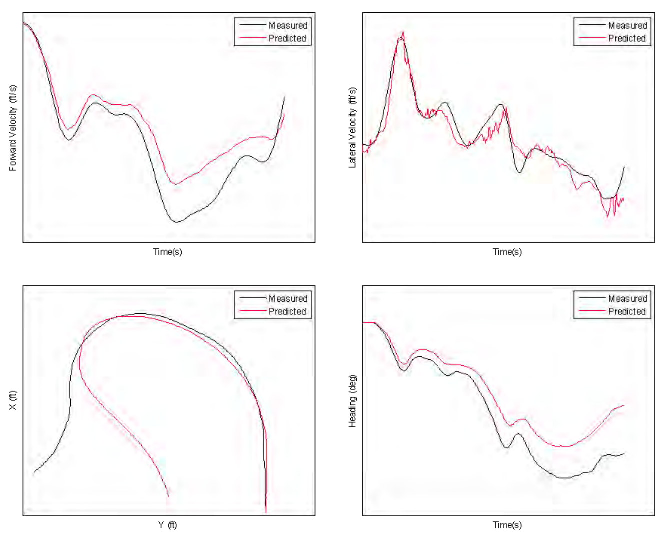

Fig. 11. Parameters characterizing a port turn (training data).

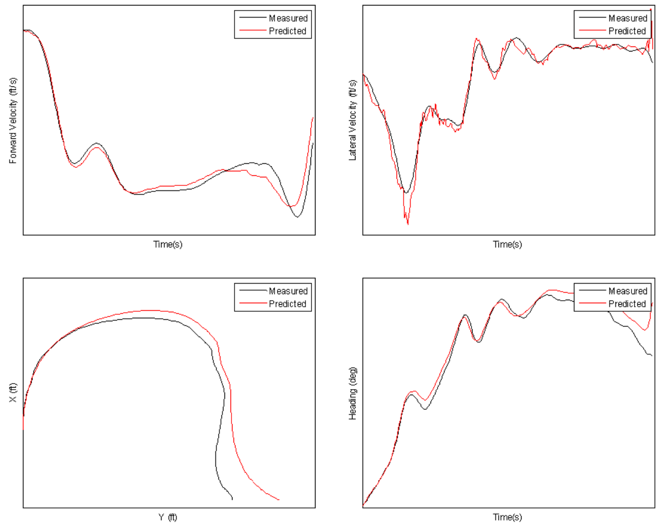

Fig. 12. Parameters characterizing a starboard turn (training data).

APPENDIX – THE AVERAGE ANGLE MEASURE

The Average Angle Measure was developed by the Maneuvering Certification Action Team at NSWCCD in 1993-1994 and some details may be found in the paper by Ammeen (1994). This metric was created in order to quantify (with a single number) the accuracy of a predicted time series when compared with the actual measured time series. The measure had to satisfy certain criteria; it had to be symmetric, linear, bounded, have low sensitivity to noise and agree qualitatively with a visual comparison of the data.

The definition is given in Eq. (A1) for the j^{th} output variable computed over a set of N points and is described as follows. Given a predicted value, p, and an experimentally measured value, s, one can plot a point in p-s space as shown in Fig. A1.

$$AAM_j = 1 - \frac{4}{\pi}\left[\frac{\sum_{n=1}^{N} D_j(n)\left|\alpha_j(n)\right|}{\sum_{n=1}^{N} D_j(n)}\right],$$

$$\alpha_j(n) = \cos^{-1}\left[\frac{\left|s_j(n)+p_j(n)\right|}{\sqrt{2}\,D_j(n)}\right], \qquad . \qquad \text{(A1)}$$

$$D_j(n) = \sqrt{s_j^2(n)+p_j^2(n)} \ ,$$

If the prediction is perfect, then the point will fall on a 45° line extended from the origin; the distance from the origin will depend upon the magnitude of s. If $p \neq s$, the point will fall on one side or the other of the 45° line. If one extends a line from the origin such that it passes through this point, one can consider the angle between this new line and the 45° line, measured from the 45° line. This angle is a measure of the error of the prediction. To extend this error metric to a set of N points, one computes the average angle of the set. A problem arises, however. When s is small and p is relatively close to s, one may still obtain a comparatively large angle. On the other hand, when s is large and p is relatively far from s, one may obtain a relatively small angle. To correct this, the averaging process is weighted by the distance of each point from the origin. The statistic is then normalized to give a value between -1 and 1. A value of 1 corresponds to perfect magnitude and phase correlation, -1 implies perfect magnitude correlation but 180° out of phase and zero indicates no magnitude or phase correlation. This metric is not perfect; it gives a questionable response for maneuvers with flat responses, predictions with small constant offsets and small magnitude signals. Nevertheless, it is in most cases an excellent quantitative measure of agreement.

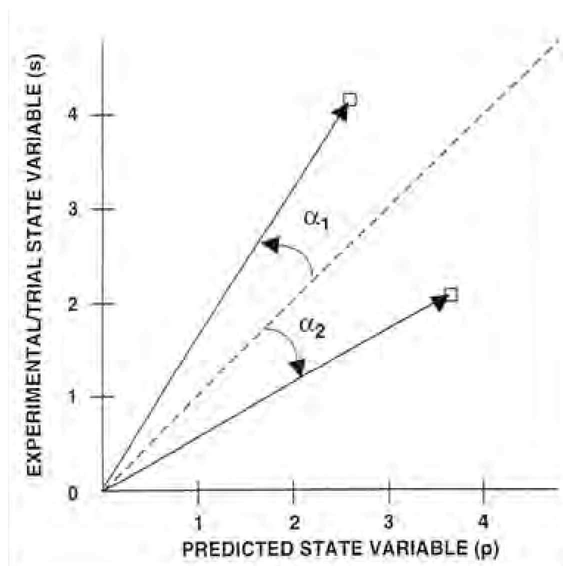

Fig. A1. Definition of the Average Angle Measure

REFERENCES

Ammeen, E.S. (1994). "Evaluation of Correlation Measures," Naval Surface Warfare Center Report, CRDKNSWC-HD-0406-01, pp. 1-65.

Faller, W.E., Hess, D.E., Fu, T.C. and Ammeen, E.S. (2008). "Fast Time-Domain Nonlinear Simulations of Ship Motions in Extreme Waves Using a New Formulation for the Wave Elevation," Proceedings of the 27th Symposium on Naval Hydrodynamics, Seoul, Korea.

Federation of American Scientists, (2000). Military Analysis Network, DOD-101 – An Introduction to the Military, US Weapon Systems, US Navy Ships, Landing Craft, Air Cushion, http://www.fas.org/man/dod-101/sys/ship/lcac.htm.

Hess, D.E., Faller, W.E., Lee, J., Fu, T.C. and Ammeen, E.S. (2006). "Ship Maneuvering Simulation in Wind and Waves: A Nonlinear Time-Domain Approach Using Recursive Neural Networks," Proceedings of the 26th Symposium on Naval Hydrodynamics, Rome, Italy.

Hess, D.E., Faller, W.E., Minnick, L. and Fu, T.C. (2007). "Maneuvering Simulation of *Sea Fighter* Using A Fast Nonlinear Time Domain Technique," Proceedings of the 9th International Conference on Numerical Ship Hydrodynamics, Ann Arbor, Michigan.

Hess, D.E., Faller, W.E., and Fu, T.C. (2009). "Neural Network Models of Forces and Moments on a Model of LCAC," Proceedings of the 47th AIAA Aerospace Sciences Meeting, Orlando, FL.

Mantle, P.J. (1980). "Air Cushion Craft Development,", Mantle Engineering Co., Inc., David W. Taylor Naval Ship Research and Development Center, Systems Development Department Evaluation Report, DTNSRDC – 80/012.

Mantle, P.J. (1975). "A Technical Summary of Air Cushion Craft Development,", David W. Taylor Naval Ship Research and Development Center, Systems Development Department Evaluation Report, DTNSRDC – 4727.

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